Implementation of Image Segmentation on Digital Images using Modified Otsu Algorithm

Brijesh Shah, Akshaya Patel, Satish Shah

Abstract— The first step in image analysis is segment the image. Segmentation subdivides an image into its constituent regions or objects. Among all Segmentation Techniques, the Thresholding methods are widely used because of their advantages of simple implement and time saving. Thresholding method is based on a threshold value. The key of this method is to select the threshold value. An Otsu method is one of the superior threshold selection methods. Image segmentation based on Otsu's method and modified Otsu algorithms are thoroughly presented in the paper.

Index Terms— Image segmentation, Threshold selection, Histogram, Otsu's method.

I. INTRODUCTION

Image segment is a basic component of many computer vision systems. Automatic thresholding is an important technique in image segmentation and machine vision applications. The basic idea of automatic thresholding is to automatically select an optimal gray-level threshold value for separating objects of interest in an image from the background based on their gray-level distribution. While humans can easily differentiable an object from complex background and image thresholding is a difficult tasks for separate them. The gray-level histogram of an image is usually considered as efficient tools for development of image thresholding algorithms. The main objective is to determine a threshold for bi-level thresholding or several thresholds for multi-level thresholding for image segmentations [1].Several algorithms of multilevel thresholding have been proposed. The OTSU algorithm (Maximization of interclass variance) is one of the superior threshold selection methods. Otsu's method of image segmentation selects an optimum threshold by maximizing the between-class variance in a gray image.

II. THE OTSU'S METHOD

Otsu Thresholding was proposed in 1979. Otsu is also called maximum variance between clusters. Image histogram as the basis and maximum variance between target and background as the selection criteria. It uses discriminant analysis to divide foreground and background by maximizing the discriminant measure.

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The threshold operation is regarded as the partitioning of the pixels of an image into two classes such as objects and background at grey-level *t*, and an optimal threshold point can be determined by minimizing equations using within-class variance, between-class variance, and the total variance[2]. Threshold segmentation is a method that separates an image into a number of meaningful regions through the selected threshold values. Let the pixels of a given picture be represented in *L* gray levels [0, *L-1*]. The number of pixels at level *i* is denoted by n_i and the total number of pixels by $N = n_0 + n_1 + n_2 + ... + n_{L-1}$.

The probability of gray *i* is

$$p_i = \frac{n_i}{N},\ p_i \geq 0, \sum_{i=1}^{L} p_i = 1.$$

Now suppose that we dichotomize the pixels into two classes *C*0 and *C*1 (background and objects, or vice versa) by a threshold at level t, *C0* denotes pixels with levels [1: t], and *C*1 denotes pixels with levels [t+1: L]. Then the probabilities of class occurrence and the class mean levels, respectively, are given by:

The probability of target is $w_0(t) = \sum_{i=0}^{t} p_i$

The w_0 is regarded as the zeroth-order cumulative moment of the class c_0.

The probability of back ground is $w_1(t) = \sum_{i=t+1}^{L-1} p_i$

The w_1 is regarded as the zeroth-order cumulative moment of the class c_1.

The mean of target is $\mu_0(t) = \sum_{i=0}^{t} ip_i / w_0$

The mean of background is $\mu_1(t) = \sum_{i=t+1}^{L-1} ip_i / w_1$

For any given threshold, the total variance σ_T^2 is the sum of the within-class variances

(weighted) σ_W^2 and the between class variance σ_B^2 ,as shown below:

$$\sigma_T^2 = \sigma_B^2 + \sigma_W^2$$

Where,

The within-class variance: $\sigma_W^2 = w_0\sigma_0^2 + w_1\sigma_1^2$

Where, the class variances are given by:

$$\sigma_0^2(t) = \sum_{i=0}^{t} (i-\mu_0)^2 \frac{p_i}{w_0}$$

$$\sigma_1^2(t) = \sum_{i=t+1}^{L-1} (i-\mu_1)^2 \frac{p_i}{w_1}$$

The variance between the two classes is:

$$\sigma_B^2(t) = w_0(t)w_1(t)(\mu_0(t)-\mu_1(t))^2$$

The total variance of the levels is:

$$\sigma_T^2(t) = \sum_{i=0}^{L-1} (i-\mu_T)^2 p_i$$

Where, Total mean of the Image is:

$$\mu_T = \sum_{i=0}^{L-1} ip_i = \mu_0 w_0 + \mu_1 w_1$$

Since the total is constant and independent of t, so, minimizing the within-class variance σ_W^2 is the same as maximizing the between-class variance σ_B^2.

In order to evaluate the "goodness" of the threshold (at level t), we shall introduce the following discriminant criterion measures (or measures of class separability) used in the discriminant analysis:

$$\eta = \frac{\sigma_B^2(t)}{\sigma_T^2(t)}$$

The optimal threshold t*that maximizes η, or equivalently maximizes $\sigma_B^2(t)$, is selected by using:

$$\eta = \frac{\sigma_B^2(t)}{\sigma_T^2(t)}$$

Where, $\sigma_B^2(t) = \dfrac{[\sigma_T^2(t)w_0(t)-\mu_T]^2}{w_0(t)[1-w_0(t)]}$

And, the optimal threshold t*is: $\sigma_B^2(t^*) = \max d(t), 0 \le t \le L-1$

Assuming that there are k thresholds, {t1, t2, …, tk}, which divide the original image into k classes: C1 for [0,…, t1], C2 for [t1+1, …, t2], … , Ci for [t i-1+1, …, t i], …, and Ck for [tk-1+1, …, L-1], So the multi-threshold segmentation as following,

$$\begin{aligned}\sigma_B^2(t_1,t_2,......t_k) = {} & w_0w_1(u_0-u_1)^2+....+w_0w_k(u_0-u_k)^2+\\ & w_1w_2(u_1-u_2)^2+....+w_1w_k(u_1-u_k)^2+\\ & w_2w_3(u_2-u_3)^2+....+w_{k-1}w_k(u_{k-1}-u_k)^2\end{aligned}$$

$$w_{n-1}(t) = \sum_{i=t_{n-1}+1}^{t_n} p_i ,$$

$$u_{n-1}(t) = \sum_{i=t_{n-1}+1}^{t_n} ip_i / w_{n-1} ,$$

$$1 \le n \le (k+1).$$

The optimal thresholds $t_1^*, t_2^*, ...t_k^*$ make the total variance maximum. That is：

$$t_1^*, t_2^*, ...t_k^* = \text{Argmax}_{0 \prec t_1 \prec t_2 \prec ....\prec t_k} \sigma_B^2(t_1, t_2, ...t_k).$$

Thus, by use of Otsu, multi-threshold segmentation would be summarized as a optimization problem of the optimal thresholds, $t_1^*, t_2^*, ...t_k^*$.

III. A MODIFIED OTSU IMAGE SEGMENT METHOD

The probability distribution is used in Otsu thresholding segmentation. I increase the probability of gray levels by modifying the probability equation, so the weight and mean of the classes are also modified and so the variance between the classes is also change. Let the pixels of a given picture be represented in *L* gray levels [0, *L-1*]. The number of pixels at level *i* is denoted by n_i and the total number of pixels by $N = n_0 + n_1 + n_2 + ... + n_{L-1}$.

The probability of gray *i* is:

$$p_i = \frac{n_i}{\max(N)}$$

ALGORITHM:

1. Compute histogram and probabilities of each intensity level
2. Set up initial $\omega_i(0)$ and $\mu_i(0)$
3. Step through all possible thresholds t=1….maximum intensity
    1. Update ω_i and μ_i
    2. Compute $\sigma_b^2(t)$
4. Desired threshold corresponds to the maximum $\sigma_b^2(t)$

IV. EXPERIMENTS AND RESULTS

Several examples of experimental results are shown in figures. Throughout these figures, Figs. A (First column) are original graylevel images; Figs. B (Second column) are segment results using Otsu; and Figs. C (Third column) are segment results using modified Otsu.

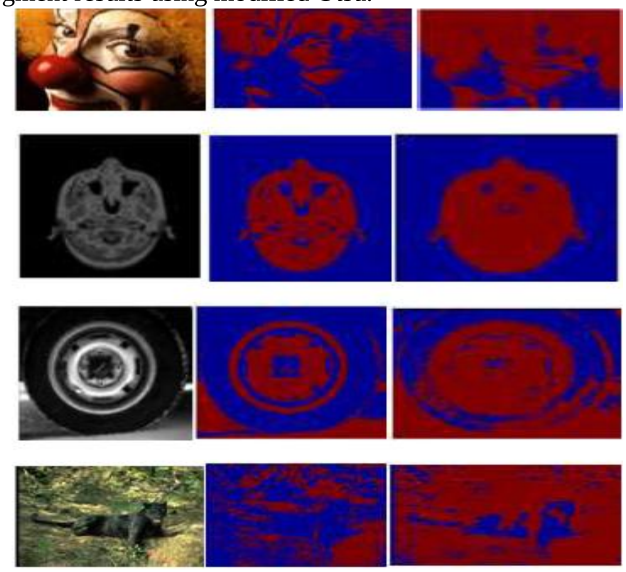

Fig A Fig B Fig C

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V. CONCLUSIONS

This paper proposed a modified Otsu algorithm. Our tests show that, a modified version of Otsu's thresholding method provides better results. Means this algorithm segment object from the background perfectly. The execution time of the modified Otsu's method is less compare to existing otsu's method. Modified OTSU techniques they are simple to implement compared to other methods. It detects the object without noise effect and its detecting sharp edges compared to existing algorithm.

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